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ABSTRACT

The practice of sourcing service inputs from overseas suppliers has been growing in response to new technologies that have made it possible to trade in some business and computing services that were previously considered non-tradable. This paper estimates the e?ects of o?shoring on productivity in US manufacturing industries between 1992 and 2000. It finds that service o?shoring has a significant positive e?ect on productivity in the US, accounting for around 10 percent of labor productivity growth during this period. O?shoring material inputs also has a positive e?ect on productivity, but the magnitude is smaller accounting for approximately 5 percent of productivity growth.

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1. Introduction

New technologies are making it increasingly possible for firms to source their service inputs from suppliers abroad. Recent examples include call centers in India, as well as some more skill intensive tasks such as computer software development. The practice of global production networks has been commonplace for decades. In the OECD, the use of imported inputs in producing goods that are exported accounted for 21 percent of trade in 1990, and this grew by 30 percent between 1970 and 1990 (see Hummels, Ishii and Yi, 2001).[1] However, until recently, global production networks mostly involved the offshoring of manufactured intermediate inputs, whereas now many services that were previously seen as non-tradable have become tradeable.[2] Whilst service offshoring by manufacturing industries in the US is still at fairly low levels, the practice is growing rapidly, at an average annual rate of 6.3 percent between 1992 and 2000.[3] (See Table 1). Yet the empirical evidence on the effects of service offshoring is scant. In this paper we estimate whether there are any benefits of offshoring in the form of productivity growth.[4]

Offshoring can increase productivity either due to compositional or structural changes. If a firm relocates its relatively inefficient parts of the production process to another country, where they can be produced more cheaply, it can expand its output in stages it has comparative advantage. In this case, the average productivity of the remaining workers increases due to the change in the composition of the workforce. Moreover, structural changes that in-

[1] The fragmentation of production stages has been widely studied within a trade theoretic framework by Dixit and Grossman (1982), Jones and Kierzkowski (1990, 1999, 2001), Deardorff (1998, 2001), Cordella and Grilo (1998), Amiti (2005) and others. This same phenomenon has also been referred in the literature as international production sharing, globalized production, de-localization, slicing up the value chain and offshoring. Some authors go on to distinguish between who owns the production stage abroad: when it is owned by the same firm it is referrred to as vertical FDI or intra-firm trade; and when it is owned by a foreign firm is it referred to as arms length trade or international outsourcing. Antras and Helpman (2004) distinguish between domestic and international outsourcing.

[2] This increasing practice of service offshoring has led to strong opposition. Support for free trade among white collar workers with incomes over $100,000 slid from 57 percent in 1999 to 28 percent in 2004, according to a study by the University of Maryland. Furthermore, on March 4, 2004, the US Senate passed restrictions on offshoring by barring companies from most federal contracts if they planned to carry out any of the work abroad. Some exceptions were to apply, for example defence, homeland security and intelligence contracts deemed necessary for national security, but this legislation was not passed in the House.

[3] See Amiti and Wei (2005a) for world trends in service offshoring.

[4] Note that we do not undertake an overall welfare analysis, and recognize that there could be negative effects such as a deterioration in the terms of trade. See Samuelson (2004).

crease the productivity of the remaining workers are also likely. These benefits can arise due to offshoring material inputs or service inputs due to the access of new input varieties. However, even larger benefits are likely to arise from offshoring service inputs, such as computing and information services, either due to workers becoming more efficient from restructuring or through firms learning to improve the way activities are performed from importing a software package, for example. We estimate the effects of both service and material offshoring on productivity.

Measuring offshoring by industry requires detailed input/output tables. These are provided on an annual basis for the period 1992 to 2000 by the Bureau of Labor Statistics (BLS) for the US economy. We combine the input/output information with trade data, to measure service and material offshoring, defined as the share of imported services and materials, respectively, analogous to the measure of material offshoring in Feenstra and Hanson (1999). Thus our measure includes imports from affiliated and unaffiliated firms. Total factor productivity (TFP) and labor productivity are also measured using data from the BLS. The data are aggregated up from 450 SIC manufacturing industries to 96 manufacturing industries in order to match the level of aggregation of the input/output (I/O) tables, which provides details of service inputs. It is important to net out service inputs when calculating productivity in order to avoid conflating measures due to missing inputs. Labor productivity in manufacturing grew at an annual average rate of 4 percent between 1992 and 2000.

The results show that service offshoring has a significant positive effect on productivity in the manufacturing sector. It accounts for around 10 percent of labor productivity growth over the sample period. These results are robust to including additional controls such as the use of high technology capital, and the share of total imports. The instrumental variables estimates indicate a slightly larger positive productivity effect from service offshoring than those indicated by OLS. Material offshoring also has a positive effect on productivity but this was not robust across all specifications, and the magnitude of the effects is lower than service offshoring, only accounting for 5 percent of total labor productivity growth between 1992 and 2000.

This is the first comprehensive study to find a link between service offshoring and productivity.[5] There is only one other study on productivity and international offshoring of

[5] A number of other studies have focused on employment effects from offshoring. For example, Amiti

services in the US (see Mann, 2004),[6] which is a "back of the envelope" type calculation and considers only the IT industry. Mann calculates that offshoring in the IT industry led to an annual increase in productivity of 0.3 percentage points for the period 1995 to 2002, which translates into a cumulative effect of $230 billion in additional GDP.[7] There have been a few more studies on the productivity effects of offshoring using European data. Gorg and Hanley (2003) find that service offshoring had a positive impact on productivity in the electronics industry in Ireland between 1990 and 1995. However, this affect disappears when they extend the study to all manufacturing industries in Ireland, and over a longer period, between 1990 and 1998 (see Gorg *et al* , 2005). A related study by Girma and Gorg (2004) finds positive evidence of service outsourcing on labor productivity and total factor productivity in the UK between 1980 and 1992, but this study does not distinguish between domestic and foreign outsourcing, and the study only covers three manufacturing industries.[8] In contrast, we focus on international sourcing of inputs and our data covers all manufacturing industries in the US.

The rest of the paper is organized as follows. Section 2 sets out the model and estimation strategy. Section 3 describes the data. Section 4 presents the results and Section 5 concludes.

2. Model and Estimating Framework

This section describes a conceptual framework that motivates the empirical specification.[9]

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and Wei (2005b) shows that offshoring has a small negative effect on employment using disaggregated manufacturing industry data (450 industries) in the US. However, this affect disappears at a more aggregated level of 96 industries indicating that there is sufficient growth in demand in other industries within these broadly defined classifications to offset any negative effects. Harrison and McMillan (2005) report correlations between US multinational employment at home and abroad. Other studies such as Ekholm and Hakkala (2005) go on to disentangle the employment effects by skill, using Swedish data.

[6] Ten Raa and Wolff (2001) find evidence of positive effects of domestic outsourcing on US manufacturing productivity – it explains 20% of productivity growth, but does not consider the effects of international outsourcing.

[7] This is calculated as follows: globalization led to a fall of 10 to 30 percent in prices of IT hardware; taking the mid-point of 20% times the price elasticity of investment equals the change in IT's investment to productivity growth. See footnote 5 in Mann (2004).

[8] Egger and Egger (2005) study the effects of international outsourcing of materials inputs. They find that material input outsourcing has a negative effect on productivity of low skilled workers in the short-run but a positive effect in the long-run. They found that international outsourcing contributed to 3.3% of real value added per low-skilled worker in the EU from 1993 to 1997. They attribute the negative short-run effect to imperfections in the EU labor and goods markets. However, they do not include services in their study.

[9] This framework is consistent with the theoretical model developed by Mitra and Ranjan (2007).

2.1. Model

The production function for an industry i is given by

$$Y_i = A_i(oss_i, osm_i)F(L_i, K_i, M_i, S_i), \tag{2.1}$$

where output, Y_i, is a function of labor, L_i, capital, K_i, materials, M_i, and service inputs, S_i. The technology shifter, A_i, is a function of offshoring of services (oss_i), and offshoring of material inputs (osm_i).

There are at least four possible channels through which offshoring can affect productivity, A_i: (i) a static efficiency gain; (ii) restructuring; (iii) learning externalities; and (iv) variety effects. First, when firms decide to outsource materials or services to overseas locations they relocate the less efficient parts of their production stage, so average productivity increases due to a compositional effect. Second, the remaining workers may become more efficient if offshoring makes it possible for firms to restructure in a way that pushes out the technology frontier. This is more likely to arise from offshoring of service inputs, such as computing and information, rather than offshoring of material inputs. Third, efficiency gains might arise as firms learn to improve the way activities are performed by importing services. For example, a new software package can improve the average productivity of workers.[10] Fourth, productivity could increase due to the use of new material or service input varieties as in Ethier (1982). Since we cannot distinguish the exact channel of the productivity gain arising from offshoring, we will specify it in this more general way as entering A_i.

We assume that a firm chooses the total amount of each input in the first stage, and chooses what proportion of material and service inputs will be imported in the second stage. The fixed cost of importing material inputs, F_k^M, and the fixed cost of importing service inputs, F_k^S, vary by industry k. This assumption reflects that the type of services or materials required are different for each industry, and hence importing will involve different amounts of search costs depending on the level of the sophistication of the inputs.

[10] Most people would expect that learning externalities would go from the US to other countries rather than to the US, but it is in principle a possibility and there has been some evidence showing that US productivity increased as a result of inward FDI. See Keller and Yeaple (2003).

2.2. Estimation

Taking the log of equation 2.1, and denoting first differences by Δ, the estimating equation becomes

$$\begin{aligned}\Delta \ln Y_{it} &= \alpha_0 + \alpha_1 \Delta oss_{it} + \alpha_2 \Delta osm_{it} \\ &\quad + \beta_1 \Delta \ln L_{it} + \beta_2 \Delta \ln K_{it} + \beta_3 \Delta \ln M_{it} + \beta_4 \Delta \ln S_{it} + \delta_t D_t + \delta_i D_i + \varepsilon_{it}.\end{aligned} \tag{2.2}$$

This first difference specification controls for any time invariant industry specific effects such as industry technology differences. In this time differenced specification, we also include year fixed effects, to control for any unobserved time-varying effect common across all industries that affect productivity growth, and in some specifications we also include industry fixed effects. Some industries may be pioneering industries that are high growth industries and hence more likely to outsource; and some industries might be subject to higher technical progress than others. Adding industry fixed effects to a time differenced equation takes account of these factors, provided the growth or technical progress is fairly constant over time. We estimate equations 2.2 using ordinary least squares, with robust standard errors corrected for clustering. We hypothesize that α_1 and α_2 are positive. We also include one period lags of the offshoring variables to take account that productivity effects may not be instantaneous.[11]

There are a number of econometric issues that will need to be addressed. First, the choice of inputs is endogenous. To address this, we estimate the total factor productivity equation using the Arrellano-Bond (1991) GMM estimator, which uses all possible lags of each variable as instruments.[12] An alternative way to address the endogeneity of inputs is to estimate productivity as value added per worker. Since the dependent variable is redefined as real output less materials and services, divided by labor, the inputs would not be included as explanatory variables.

Second, there may also be a problem of potential endogeneity of offshoring. High productivity firms may be the ones that are more likely to engage in global production strategies which could lead to reverse causality. Alternatively, it could be the low productivity firms

[11] Longer lags were insignificant.

[12] We do not use the Olley-Pakes or Levinsohn-Petrin methodology to address the endogeneity of inputs because those approaches require firm-level data whereas our data is at the industry level.

that engage in offshoring in the expectation that this would improve productivity, hence it is unclear which way the bias would go. If the same set of firms are most likely to engage in offshoring over the sample period then industry fixed effects in a time differenced equation would suffice. However, if there are time varying factors that affect offshoring and productivity growth then it is necessary to instrument for offshoring. Unfortunately, valid instruments for offshoring are unavailable thus we also use the Arellano-Bond GMM estimator, which uses lags as instruments, to also address the potential endogeneity of offshoring.[13]

3. Data and measurement of offshoring

We estimate the effects of offshoring on productivity for the period 1992 to 2000. Service offshoring ($oss_{i,t}$) for each industry i at time t is defined as the share of imported service inputs. Since imports of service and materials inputs by industry are not available, we follow Feenstra and Hanson (1996, 1999) to calculate a proxy for service offshoring as follows:

$$oss_{it} = \sum_j \left[\frac{\text{input purchases of service } j \text{ by industry } i,\ \text{at time } t}{\text{total non-energy inputs used by industry } i,\ \text{at time } t}\right] * \left[\frac{\text{imports of service } j\text{, at time } t}{\text{production}_j + \text{imports}_j - \text{exports}_j \text{ at time } t}\right]. \tag{3.1}$$

The first square bracketed term is the share of service inputs as a proportion of total non-energy inputs, calculated using annul input/output tables from 1992 to 2000 constructed by the Bureau of Labor Statistics (BLS), based on the Bureau of Economic Analysis (BEA) 1992 benchmark tables. The BEA use SIC 1987 industry disaggregation, which consist of roughly 450 manufacturing industries. These are aggregated up to 96 input/output manufacturing codes by the BLS.[14] We include the following five service industries as inputs to the manufacturing industries: telecommunications, insurance, finance, business services, and computing and information. From column 1 in Table 2, we see that business services is the largest component of service inputs with an average share of 12% in 2000; then finance

[13] Of course, if these variables are correlated over time any endogeneity that exists will persist.

[14] We were unable to use the more disaggregated BEA I/O tables because the next available year is 1997 and this is under a different classification system, called NAICS. Unfortunately, the concordance between SIC and NAICS is not straightforward, thus there would be a high risk that changes in the input coefficients would reflect reclassification rather than changes in input intensties. In contrast, the BLS I/O tables use the same classification throughout this period.

(2.4%); telecommunications (1.3%); insurance (0.5%); and the lowest share is computing and information (0.4%). There is much variation between industries. For example, in 2000, business services only accounted for 2 percent in the "household audio and video equipment" industry whereas business services accounted for 33 percent of total non-energy inputs in the "ophthalmic goods" industry.

The service industries were aggregated up to these five service categories to match the international trade data in the IMF Balance of Payments yearbooks: the share of imports of services is calculated by applying the economy-wide import share to each industry (the second bracketed term in equation 3.1). In the last column of Table 2, we see that the import share of all service categories, except communications, increased over the period.

To illustrate how offshoring is calculated, note from Table 2 that the US economy imported 2.2 percent of business services in 2000. We assume that each manufacturing industry imported 2.2 percent of its business service that year. Thus, on average, the offshoring of business services is equal to 0.12*0.022=0.3 percent. We aggregate across the five service inputs to get the average service offshoring intensity for each industry, oss_{it}. An analogous measure is constructed for material offshoring, denoted by osm_{it}. From Table 1, we see that service offshoring in 2000 was only 0.3 percent whereas the material offshoring was 17.4 percent. It should not be surprising that service offshoring in manufacturing is small given that total service inputs make up only a small share of total inputs in manufacturing. Both types of offshoring have been increasing over the sample period, with higher growth rates for service offshoring at an annual average of 6.3 percent compared to an average growth rate of 4.4 percent for material offshoring.

There are a number of potential problems with these offshoring measures that should be noted. First, they are likely to under-estimate the value of offshoring because the cost of importing services is likely to be lower than the cost of purchasing them domestically. While it would be preferable to have quantity data rather than current values this is unavailable for the United States. Second, applying the same import share to all industries is not ideal, but given the unavailability of imports by industry this is our "best guess". The same strategy was used by Feenstra and Hanson (1996, 1999) to construct measures of material offshoring. This approach apportions a higher value of imported inputs to the industries that are the biggest users of those inputs. Although this seems reasonable, without access to actual import data by industry it is impossible to say how accurate it is. Despite these limitations, we believe that combining the input use information with trade data provides a reasonable proxy of the proportion of imported inputs by industry.

The BLS data sources are used for estimation of productivity to match the level of aggregation of the offshoring ratios. However, capital stock was only available from the Annual Survey of Manufacturers (ASM) at the SIC level so needed to be aggregated up to the BLS I/O level. We adopt the perpetual inventory method to extend the capital stock series beyond 1996, using average depreciation rates that were applied in the NBER (Bartelsman and Gray, 1996) database: 7.7 percent depreciation for equipment and 3.5 percent for structures. Productivity is estimated at the more aggregate BLS I/O industry level because service inputs by industry are only available from the I/O tables and these need to be subtracted from gross output in order to ensure that productivity growth is not inflated in service-intenstive industries as an artifact of an omitted variable. All the summary statistics are provided in Table 3.

4. Results

We estimate equation 2.2 at the industry level for the period 1992 to 2000. All variables are entered in log first differences, except those that are constructed as ratios, such as service and material offshoring. All estimations include year fixed effects and some specifications also include industry fixed effects. The errors have been corrected for heteroskedasticity by clustering at the industry level.

4.1. Total Factor Productivity

The results from estimating equation 2.2 using OLS are presented in Table 4. Columns 1 to 4 include year fixed effects, and columns 5 to 9 include year and industry fixed effects. All columns show that service offshoring has a positive significant effect on total factor productivity. That is, holding all factors of production constant (total services, materials, labor and capital stock), increasing the share of service offshoring leads to higher output. In the first column we only include the change in offshoring in period t; in the second column we only include the lagged value $(t-1)$; whereas in the third column we include both the contemporaneous and lagged values of offshoring. In column 4, we split employment by production and non-production workers (proxies for unskilled and skilled workers respectively), to ensure that changes in skill composition are not driving the results.[15] We find this breakdown hardly affects the size of the offshoring coefficients. In each specification, service offshoring is individually significant in the current and lagged periods, and jointly significant, with a p-value less than 0.01. Similarly, service offshoring is positive and significant in columns 5 to 8 with industry effects, with the coefficients now larger. The coefficient on material offshoring is positive and significant only in some of the specifications.

The endogeneity of input choices could result in biased estimates using OLS estimation. To address this issue, we re-estimate equation 2.2 using the Arrellano-Bond dynamic panel estimation technique in column 9. In this specification, all possible lags of each variable are used as instruments, and the lagged dependent variable is also included but this is insignificant. The coefficient on service offshoring remains positive and significant, with the size of the joint effect of the current and lagged offshoring variables a little smaller than the coefficients in the OLS estimation. The effect of material offshoring is now higher, with the lagged coefficient positive and significant.

4.2. Labor Productivity

An alternative way to address the endogeneity of labor, material and service inputs is to estimate the effect of offshoring on labor productivity. This is measured by value added per worker, calculated by taking the difference between real output and real materials and services, divided by employment. The results are presented in Table 5.[16] In columns 1 to 3, with only year fixed effects, we see that lagged service and material offshoring are positive and significant in columns 2 and 3. Once we add industry effects in columns 4 to 6, the size of the coefficients on service offshoring become larger, and both the contemporaneous and lagged variables are significant, however material offshoring becomes insignificant.

[15] This was the most detailed skill level data available.

[16] All specifications include capital stock as an explanatory variable. However, estimates without capital stock produce the same results.

4.2.1. Additional Controls

There may be concern that the service offshoring measure is correlated with omitted variables such as high-technology capital or total imports, which may be inflating the coefficients on service offshoring. To address this we include a measure of high technology capital as in Feenstra and Hanson (1999); and the share of imports by industry. The data for high-technology capital stock are estimates of the real stock of assets within two-digit SIC manufacturing industries, from the BLS. High-technology capital includes computers and peripheral equipment, software, communication equipment, office and accounting machinery, scientific and engineering instruments, and photocopy and related equipment. Each capital asset is then multiplied by its ex post rental price to obtain the share of high-tech capital services for each asset within each two-digit SIC industry (also estimated by BLS), and reflects the internal rate of return in each industry and capital gains on each asset.[17]

The high-tech capital share measured with ex post rental prices is included in column 1 of Table 6, and turns out to be insignificant. Import share, defined as the ratio of total imports to output by industry, is included in column 2. This shows that tougher import competition has a positive effect on labor productivity, but its inclusion leaves the effect of service offshoring unchanged. In columns 3 and 4 we include industry effects and, again, we find that the service offshoring coefficients are significant and larger with industry effects in columns 4 and 5; the coefficient on lagged material offshoring is also significant with fixed industry effects. We see from column 4 that the high-tech capital becomes significant at the 10% level yet the import share with industry fixed effects, in column 4, becomes insignificant. Although the high-tech capital share, with industry fixed effects, has a positive effect on labor productivity it does not affect the size of the service offshoring coefficients.

With industry level data and a short time series there is concern that outlier industries might be driving the results. To check that this is not the case here we reestimate the equation using robust regressions in columns 5 of Table 6 – this uses an iterative process, giving less weight to outlier observations.[18] The service offshoring coefficients are still significant but

[17] Alternatively, the capital stock components can be multiplied by an ex ante measure of rental prices used by Berndt and Morrison(1995), where the Moody rate of Baa bonds is used to measure the ex ante interest rate and the capital gains term is excluded. However, these measures were insignificant in every specification and thus are not included to save space.

[18] Using the rreg command in STATA, an intial screening is performed based on Cook's distance >1

the point estimates are now smaller. Inspection of the data reveals that the tobacco industry is the main outlier. Omitting tobacco from the estimation (in column 6) provides similar results to the robust regressions. To ensure that no one industry is driving the results, we drop tobacco from the subsequent estimations.

4.2.2. Sensititivity: Endogeneity

A more general specification would allow for a lagged dependent variable, but this would result in a correlation with the error term, which is particularly problematic in a fixed effects model. Thus, as a final robustness check on the labor productivity estimates we re-estimate the equations using Arrellano-Bond GMM analysis. We also include the high-tech capital share and import share variables in all estimations. In Table 7 we use all lagged variables as instruments. The results show that service offshoring and high-tech capital share have a positive significant effect on labor productivity, material offshoring has a positive insignificant effect, and import share has a negative effect. In all of the specifications, service offshoring has a positive and significant effect on productivity whereas material offshoring has an insignificant effect.

4.3. Discussion of Results

To get an idea of the magnitude of the effects, we calculate the total effect of service offshoring on labor productivity using the coefficients from the last column in Table 6 and those from the GMM estimates in Table 7, which range from 0.26 to 0.67. Service offshoring increased by 0.1 of a percentage point over the sample period, from 0.18 to 0.29 (see Table 1) so this implies that service offshoring led to an increase of between 2.6 to 6.7 percent in labor productivity over the sample period. Taking the mid-point between these estimates (of 0.46) and given that value added per worker increased by an average of 46 percent over the sample period, this suggests that service offshoring accounted for 10 percent of the average growth in labor productivity.[19] In contrast material offshoring either had an insignificant effect on

to eliminate gross outliers before calculating starting values, followed by an iterative process: it performs a regresssion, calculates weights based on absolute residuals, and regresses again using those weights, beginning with Huber weights followed by biweights as suggested by Li (1985).

[19] The averages are weighted by value added - the overall service offshoring effect is calculated as $(0.46 * 0.1)/0.46$.

labor productivity or a much smaller positive effect: taking the mid-point of the material coefficients from the specifications where material offshoring was significant we find that material offshoring contributed 5 percent to labor productivity.

Given the small size of service offshoring it might appear surprising to find such a sizeable significant effect on productivity. This could be due to large compositional effects, such as labor being reallocated from providing services to the manufacturing plant to performing some other function. This could involve a shrinkage of the workforce in a plant, and increasing the average productivity of the remaining workers or exit of a plant, thus increasing the average productivity of the remaining plants. As well as compositional changes, service offshoring might enable a reorganization of the remaining workers thus increasing their efficiency. It was not possible to assess the mechanism for this growth as firm level data with service offshoring information was unavailable.

The question then arises as to why the effect from material offshoring was insignificant or smaller than service offshoring? A plausible explanation for this result is that there may be decreasing returns from scale from offshoring. Material offshoring has been in practice for many decades and is at fairly high levels whereas the practice of service offshoring is more recent. It is possible that many of the productivity benefits from material offshoring have been exhausted. Moreover, the possibility for firms to restructure in a way that pushes out the technology frontier is more likely to arise from offshoring of service inputs, such as computing and information, rather than offshoring of material inputs.

5. Conclusion

Sourcing service inputs from abroad by US firms is growing rapidly. Although the level of service offshoring is still low compared to material offshoring, this business practice is expected to grow as new technologies make it possible to access cheaper foreign labor and different skills. Thus it is important to understand its effects on the domestic economy. In this paper, we analyzed the effects of service and material offshoring on productivity in manufacturing industries in the US between 1992 to 2000. We found that offshoring has a positive effect on productivity: service offshoring accounts for around 10 percent of labor productivity growth over this period; and material offshoring 5 percent of labor productivity.

Our analysis suggests a number of possible avenues for future research. First, data limitations have prevented us from identifying the channels through which service offshoring has increased productivity. Improvements in the collection of data at the firm level with information distinguishing between domestic input purchases from imports, combined with detailed skill level data would be a major step forward in making this type of analysis possible. Second, as well as productivity effects, offshoring is likely to have terms of trade and income distribution effects. Feenstra and Hanson (1999) found that material outsourcing explained about 40 percent of the increase in the skill premium in the US in the 1980s. Given that service offshoring is likely to be more skill intensive than material offshoring, it will be interesting to see what effects, if any, service offshoring has on the wage skill premium.

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Table 1 Material and Service Offshoring 1992-2000

	Material offshoring- OSM		Service offshoring - OSS	
Year	%	%Δ	%	%Δ
1992	11.72		0.18	
1993	12.68	5.25	0.18	4.88
1994	13.41	5.06	0.20	6.39
1995	14.18	4.65	0.20	4.10
1996	14.32	1.75	0.21	6.64
1997	14.55	1.75	0.23	6.97
1998	14.94	2.97	0.24	6.57
1999	15.55	3.49	0.29	16.73
2000	17.33	10.12	0.29	-2.23
1992-2000		4.38		6.26

Table 2 Service Inputs, by type: 1992 and 2000

Services	Share of Service Inputs (%)				Import of Services (%)
	Mean	Std Dev	Min	Max	
(1992)					
Communication	1.16	0.79	0.25	4.82	2.47
Financial	1.91	0.63	0.93	4.72	0.25
Insurance	0.43	0.18	0.16	1.39	1.82
Other business service	9.69	7.16	1.87	37.93	1.47
Computer and Information	0.55	0.44	0.02	2.53	0.16
(2000)					
Communication	1.27	0.94	0.28	5.45	1.18
Financial	2.37	0.86	0.71	5.28	0.51
Insurance	0.47	0.22	0.10	1.36	2.84
Other business service	12.02	8.55	1.89	44.99	2.23
Computer and Information	0.38	0.31	0.01	2.01	0.62

Source: BLS, Input-Output Tables and IMF, Balance of Payments Statistics Yearbook.

Table 3 Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
$oss_{i,t}$	864	0.239	0.162	0.040	1.071
$\Delta oss_{i,t}$	768	0.016	0.032	-0.145	0.411
$osm_{i,t}$	864	14.949	9.808	1.220	69.255
$\Delta osm_{i,t}$	768	0.694	1.950	-16.173	21.220
ln(value-added per worker)$_{i,t}$	864	-2.591	0.480	-4.034	-0.526
Δln(value-added per worker)$_{i,t}$	768	0.043	0.070	-0.231	0.364
ln(real output)$_{i,t}$	864	10.112	0.953	6.549	12.979
Δln(real output)$_{i,t}$	768	0.036	0.074	-0.256	0.443
ln(materials)$_{i,t}$	864	9.032	1.034	5.577	12.498
Δln(materials)$_{i,t}$	768	0.031	0.103	-0.567	0.544
ln(services)$_{i,t}$	864	7.060	1.025	3.892	9.875
Δln(services)$_{i,t}$	768	0.045	0.075	-0.316	0.418
ln(labor)$_{i,t}$	864	11.834	0.847	8.618	13.836
Δln(labor)$_{i,t}$	768	-0.001	0.038	-0.165	0.139
ln(capital stock)$_{i,t}$	844	9.175	1.030	5.979	11.701
Δln(capital stock)$_{i,t}$	748	0.029	0.043	-0.809	0.301
$htechshare_{i,t}$	864	10.070	6.302	2.574	24.112
$\Delta htechshare_{i,t}$	768	0.265	0.959	-2.899	4.410
$impshare_{i,t}$	855	0.257	0.486	0.000	3.408
Δ(impshare)$_{i,t}$	760	0.014	0.050	-0.375	0.579

Note: (a) htechshare is defined as (high-tech capital services / total capital services). (b) all variables are entered as differences of logs except if the variable is constructed as a ratio in which case it is entered as the difference in the ratio.

Table 4 Total Factor Productivity

Dependent variable: Δln(real output)$_{i,t}$									
	OLS								GMM
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\Delta oss_{i,t}$	0.235***		0.249***	0.241***	0.341***		0.331***	0.335***	0.258***
	(0.059)		(0.042)	(0.045)	(0.051)		(0.071)	(0.073)	(0.043)
$\Delta oss_{i,t-1}$		0.094**	0.079*	0.065		0.082***	0.097***	0.093***	0.098***
		(0.036)	(0.040)	(0.041)		(0.030)	(0.027)	(0.027)	(0.019)
$\Delta osm_{i,t}$	0.001*		0.001*	0.001*	0.001		0.001*	0.001*	0.0005
	(0.001)		(0.001)	(0.001)	(0.001)		(0.001)	(0.0005)	(0.0004)
$\Delta osm_{i,t-1}$		-0.0004	0.0002	0.0002		-0.0003	0.0001	0.0001	0.0004*
		(0.0003)	(0.0003)	(0.0003)		(0.0003)	(0.0003)	(0.0003)	(0.0002)
Δln(materials)$_{i,t}$	0.389***	0.358***	0.404***	0.406***	0.432***	0.365***	0.443***	0.445***	0.432***
	(0.041)	(0.038)	(0.033)	(0.033)	(0.047)	(0.040)	(0.042)	(0.043)	(0.019)
Δln(services)$_{i,t}$	0.563***	0.592***	0.548***	0.546***	0.508***	0.566***	0.496***	0.495***	0.506***
	(0.048)	(0.042)	(0.036)	(0.036)	(0.047)	(0.043)	(0.042)	(0.042)	(0.022)
Δln(labor)$_{i,t}$	0.059***	0.056**	0.056**		0.013	0.017	0.006		
	(0.021)	(0.022)	(0.022)		(0.025)	(0.028)	(0.026)		
Δln(skilled labor)$_{i,t}$				0.029**				0.006	-0.0004
				(0.015)				(0.018)	(0.015)
Δln(unskilled labor)$_{i,t}$				0.008				-0.007	-0.003
				(0.013)				(0.013)	(0.010)
Δln(capital)$_{i,t}$	0.013	0.010	0.009	0.579*	0.001	-0.005	-0.002	0.007	-0.007
	(0.021)	(0.025)	(0.021)	(0.032)	(0.012)	(0.010)	(0.010)	(0.051)	(0.040)
Δln(real output)$_{i,t-1}$									0.009
									(0.008)
Year fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry fixed effects	no	no	no	no	yes	yes	yes	yes	no
Joint significance tests:									
$\Delta oss_t + \Delta oss_{t-1}=0$			$F(1,95)=27.99$	$F(1,95)=20.71$			$F(1,95)=21.70$	$F(1,95)=20.24$	$\chi^2(1)=31.81$
			p-value=0.00	*p-value*=0.00			*p-value*=0.00	*p-value*=0.00	*p-value*=0.00
$\Delta osm_t + \Delta osm_{t-1}=0$			$F(1,95)=2.57$	$F(1,95)=2.36$			$F(1,95)=2.19$	$F(1,95)=2.12$	$\chi^2(1)=0.64$
			p-value=0.11	*p-value*=0.13			*p-value*=0.14	*p-value*=0.15	*p-value*=0.42
Observations	748	652	652	640	748	652	652	640	541
R-squared	0.96	0.97	0.97	0.97	0.97	0.98	0.98	0.98	

Note: Robust standard errors in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%; Sargan overidentification test in column (9) estimation $\chi^2(20)=23.08$, *p-value*=0.28; and H_0: no autocorrelation $z=1.85$ Pr> z = 0.064.

Table 5 Labor Productivity

Dependent variable: $\Delta \ln(\text{value added per worker})_t$						
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta oss_{i,t}$	0.214		0.236	0.298**		0.386**
	(0.150)		(0.162)	(0.143)		(0.167)
$\Delta oss_{i,t-1}$		0.310*	0.292*		0.414**	0.418***
		(0.174)	(0.154)		(0.164)	(0.150)
$\Delta osm_{i,t}$	0.001		0.003	-0.001		0.001
	(0.002)		(0.003)	(0.003)		(0.004)
$\Delta osm_{i,t-1}$		0.003*	0.003**		0.001	0.002
		(0.001)	(0.001)		(0.001)	(0.001)
$\Delta \ln(\text{capital})_{i,t}$	0.166*	0.186*	0.196*	0.099	0.108***	0.129***
	(0.097)	(0.101)	(0.100)	(0.063)	(0.033)	(0.036)
Year fixed effects	yes	yes	yes	yes	yes	yes
Industry fixed effects	no	no	no	yes	yes	yes
Joint significance tests:						
$\Delta oss_t + \Delta oss_{t-1}=0$			$F(1,95)=3.84$			$F(1,95)=10.53$
			p-value=0.05			*p-value*=0.00
$\Delta osm_t + \Delta osm_{t-1}=0$			$F(1,95)=2.45$			$F(1,95)=0.38$
			p-value=0.12			*p-value*=0.54
Observations	748	652	652	748	652	652
R-squared	0.06	0.07	0.08	0.39	0.41	0.42

Note: Robust standard errors in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%

Table 6 Labor Productivity and Additional Controls

Dependent variable: Δln(value added per worker)$_t$	(1)	(2)	(3)	(4)	Robust regression (5)	Without tobacco industry (6)
$\Delta oss_{i,t}$	0.222	0.227	0.383**	0.394**	0.342***	0.235
	(0.171)	(0.158)	(0.171)	(0.159)	(0.077)	(0.217)
$\Delta oss_{i,t-1}$	0.289*	0.306**	0.425***	0.426***	0.266***	0.266**
	(0.150)	(0.150)	(0.138)	(0.136)	(0.075)	(0.116)
$\Delta osm_{i,t}$	0.003	0.005	0.001	0.003	0.004***	0.003
	(0.003)	(0.003)	(0.004)	(0.003)	(0.001)	(0.003)
$\Delta osm_{i,t-1}$	0.003**	0.003**	0.001	0.002*	0.002*	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Δln(capital)$_{i,t}$	0.196*	0.202**	0.130***	0.129***	0.110**	0.122***
	(0.100)	(0.101)	(0.037)	(0.036)	(0.048)	(0.038)
Δ(htechshare)$_{i,t}$	0.001		0.003	0.003	0.004*	0.003
	(0.003)		(0.003)	(0.003)	(0.002)	(0.003)
Δ(htechshare)$_{i,t-1}$	0.005		0.008*	0.008*	0.009***	0.008*
	(0.005)		(0.004)	(0.004)	(0.003)	(0.004)
Δ(impshare)$_{i,t}$		-0.142		-0.274	-0.186***	-0.270
		(0.128)		(0.182)	(0.040)	(0.187)
Δ(impshare)$_{i,t-1}$		0.158**		-0.012	0.124***	-0.011
		(0.065)		(0.059)	(0.042)	(0.058)
Year fixed effects	yes	yes	yes	yes	yes	yes
Industry fixed effects	no	no	yes	yes	yes	yes
Joint significance tests:						
$\Delta oss_t + \Delta oss_{t-1}=0$	F(1,95)=3.44	F(1,94)=4.03	F(1,95)=11.56	F(1,94)=13.47	F(1,535)=31.53	F(1,93)=6.03
	p-value=0.07	*p-value*=0.05	*p-value*=0.00	*p-value*=0.00	*p-value*=0.00	*p-value*=0.02
$\Delta osm_t + \Delta osm_{t-1}=0$	F(1,95)=2.16	F(1,94)=4.49	F(1,95)=0.22	F(1,94)=1.97	F(1,535)=10.41	F(1,93)=1.09
	p-value=0.15	*p-value*=0.04	*p-value*=0.64	*p-value*=0.16	*p-value*=0.00	*p-value*=0.30
Δ(htechsh)$_t$+Δ(htechsh)$_{t-1}$=0	F(1,95)=0.67		F(1,95)=3.09	F(1,94)=3.45	F(1,535)=9.20	F(1,93)=2.79
	p-value=0.42		*p-value*=0.08	*p-value*=0.07	*p-value*=0.00	*p-value*=0.10
Δ(impshare)$_t$+Δ(impshare)$_{t-1}$=0		F(1,94)=0.02		F(1,94)=2.52	F(1,535)=1.14	F(1,93)=2.14
		p-value=0.88		*p-value*=0.12	*p-value*=0.29	*p-value*=0.15
Observations	652	645	652	645	645	638
R-squared	0.08	0.09	0.43	0.45	0.60	0.44

Note: Robust standard errors in parentheses;* significant at 10%; ** significant at 5%; *** significant at 1%

Table 7 Labor Productivity - GMM Analysis

Dependent variable: Δln(value-added per worker)$_t$			
	(1)	(2)	(3)
Δoss_t	0.330*	0.320	0.305*
	(0.193)	(0.201)	(0.182)
Δoss_{t-1}	0.378***	0.387***	0.371***
	(0.122)	(0.122)	(0.142)
Δosm_t	-0.002	-0.002	0.002
	(0.005)	(0.005)	(0.004)
Δosm_{t-1}	0.000	0.000	0.001
	(0.001)	(0.001)	(0.001)
Δln(capital)$_t$	0.116***	0.134***	0.130***
	(0.027)	(0.028)	(0.027)
Δ(htechshare)$_t$		0.005	0.003
		(0.003)	(0.002)
Δ(htechshare)$_{t-1}$		0.009**	0.007*
		(0.004)	(0.004)
Δ(impshare)$_t$			-0.342*
			(0.181)
Δ(impshare)$_{t-1}$			-0.134
			(0.084)
Δ(vaw)$_{t-1}$	-0.199***	-0.196***	-0.276***
	(0.063)	(0.063)	(0.063)
Joint significance tests			
$\Delta oss_t + \Delta oss_{t-1} = 0$	$\chi^2(1)$= 10.80	$\chi^2(1)$= 9.75	$\chi^2(1)$= 9.06
	p-value=0.00	*p-value*=0.00	*p-value*=0.00
$\Delta osm_t + \Delta osm_{t-1} = 0$	$\chi^2(1)$= 0.04	$\chi^2(1)$= 0.07	$\chi^2(1)$= 0.60
	p-value=0.85	*p-value*=0.79	*p-value*=0.44
Δ(htechshare)$_t$ +Δ(htechshare)$_{t-1}$ = 0		$\chi^2(1)$= 4.69	$\chi^2(1)$= 3.55
(*ex post rental prices*)		*p-value*=0.03	*p-value*=0.06
Δ(impshare)$_t$ + Δ(impshare)$_{t-1}$ = 0			$\chi^2(1)$= 3.92
			p-value=0.05
Sargan test	$\chi^2(20)$= 28.65	$X^2(20)$= 29.09	$\chi^2(20)$= 29.19
	p-value=0.10	*p-value*=0.09	*p-value*=0.08
H_0 : no 2nd order autocorrelation	z =-0.22	z =-0.40	z =0.40
	p-value=0.83	*p-value*=0.69	*p-value*=0.69
Observations	550	550	544

Note: Robust standard errors in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%